

Detection of Bridges using Different Types of High Resolution Satellite Images

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Abstract— Automatic detection of geographical objects such as roads, buildings and bridges from remote sensing imagery is a very meaningful but difficult work. Bridges over water is a typical geographical object and its automatic detection is of great significance for many applications. Finding Region Of Interest (ROI) having water areas alone is the most crucial task in bridge detection. This can be done with image processing / soft computing methods using images in spatial domain or with Normalized Differential Water Index (NDWI) using images in spectral domain. We have developed an efficient algorithm for bridge detection where the ROI segmentation is done using both methods. Exact locations of bridges are obtained by knowledge models and spatial resolution of the image. These knowledge models are applied in the algorithm in such a way that the thresholds are automatically fixed depending on the quality of the image. Using the algorithm any type of bridges are extracted irrespective of their inclination and shape.

Index Terms— Fuzzy based thresholding, Region Of Interest, NDWI, Area Analysis.

I. INTRODUCTION

Earlier methods for bridge extraction from high resolution satellite imagery are based on detecting linear features after segmentation and can be applied only for very high resolution SAR images [1, 2]. Also SAR phenomena such as layover and occlusion burden the analysis and increase the false detection rate. Trias-Sanz et al., 2004 [3] suggest techniques to automatically detect bridges on small high-resolution panchromatic satellite images that rely on radiometric features (texture information) and geometric models. Using neural networks, they classify each pixel into several terrain classes. Although the approach is effective, there are several drawbacks for extending it to the general case. First, computation of texture parameters from a large image takes a significant amount of time. In addition, the analysis windows span more than one texture at the boundaries of texture regions and, therefore, give imprecise classifications. This technique also is unlikely to extract bridges over larger regions such as big rivers. Most existing methods are based on knowledge base, which is not derived automatically. But since these rules are developed by an observer, the methods are not well suited for all types of images. In the study done by Chaudhuri & Samal, 2008 [4], the image is classified into three classes, water, concrete and background using the well known facts about bridges. In the study by Gu et. al., 2011 [5], water areas are found using segmentation and possible river mask is extracted from the water regions.

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Following this step, possible bridge regions are extracted using prior knowledge and then verified using geometric constraints. In Han, Y., 2007 [6], segmentation is greatly influenced by gray level value which changes with elevation angle of sun and turbidity of water. A fuzzy based thresholding method can be used for accurately segmenting water regions from background which is suggested by Yili Fu et. al., 2009 [7]. But the knowledge model proposed in the approach cannot be applied for any complexity levels and spatial resolutions. In the method proposed by E. Gediket. al., 2012 [8], segmentation of water regions is done by NDWI and then the algorithm is preceded by the verification of certain geometric constraints.

The method described in our work, candidate bridge pixels are extracted according to area analysis and the developed bridge extraction algorithm after fuzzy based segmentation. Images in both spatial and spectral domain can be processed using this method. Results are presented and it can be observed that bridge detection is done with high accuracy for different types of images of varying complexity and resolution levels irrespective of their inclination. We have also compared the method with the ROI extraction using NDWI to validate the superior performance of our algorithm.

II. STUDY REGION

The approach of bridge detection strategy has been applied in six different satellite images of varying resolutions and different features to test the validity of the method. High-resolution satellite-based imaging sensors like IKONOS, Quickbird and SPOT provide one band of panchromatic (PAN) data (spatial domain) and four bands of multispectral (MS) data (spectral domain) at a quarter of the resolution of the panchromatic data. MS data contain four individual bands: red (R), green (G), blue (B), and near infrared (NIR). Pan-Sharpener Multispectral (PS-MS) images are obtained by fusing high resolution panchromatic and low resolution multispectral (MS) bands. This is done using Multispec32 which is a freeware multispectral image data analysis system. The resultant PSMS image has the same resolution as that of PAN image. Fig.1, fig.2, fig.3 and fig.4 are IKONOS satellite images of 1-m resolution having famous bridges of Budapest, Hungary connecting Buda and Pest across the river Danube. Fig.1 is a Pan Sharpener Multi Spectral (PS-MS) image having two bridges namely Petofi Bridge and Rakoczi Bridge crossing the river Danube. Fig.2 is another RGB satellite image of Arpad Bridge in Budapest connecting Buda and Pest. Fig.3 and fig.4 are RGB image of Margaret Bridge and PS-MS image of Chain Bridge respectively. Margaret bridge leads across to Margaret Island, situated middle of the Danube in central Budapest. Chain Bridge is a suspension bridge that spans the river Danube between Buda and Pest. Fig.5 is a Quickbird RGB image of 60cm resolution with the Tower Bridge of London over the river Thames. Fig.6 is a SPOT-5 RGB image with 4m resolution of Washington D.C. The bridge shown in the image is Woodrow Wilson Bridge which spans the Potomac river between the city of Alexandria and Oxon Hill, Maryland, United States.



Fig.1:IKONOS PS-MS Image (1m)



Fig.2:IKONOS RGB Image (1m)

III. METHODOLOGY

The algorithm based on histogram works well for most of the satellite images as the water areas have significant difference in gray level compared to other regions. But some shadow regions and urban areas can also be misclassified as water regions. Depending on sun elevation and azimuth angles and the sensor



Fig.3:IKONOS RGB Image (1m)



Fig.4:IKONOS PS-MS Image (1m)



Fig.5:Quickbird RGB Image (60cm)



Fig.6: SPOT-5 RGB Image (4m)

azimuth angle gray level intensities may vary widely and this method is not possible. Therefore, in our work, fuzzy threshold segmentation [7] is used for pre-processing the image. The overall flow of the system is shown in Fig.7.

A. Fuzzy based thresholding

Fuzzy thresholding can be applied directly on PAN images or else we have to convert to grayscale for the case of RGB/ multispectral images. If $\mu_x(x_{ij})$ represent membership value of gray value x at location (i, j) then the original image X of size (m, n) is defined as (1):

$$X = \{(x_{ij}, \mu_x(x_{ij}))\} \quad (1)$$

where $0 \leq \mu_x(x_{ij}) \leq 1$; $i = 0, 1, \dots, m - 1$; $j = 0, 1, \dots, n - 1$.

Choose an arbitrary threshold t and find $\mu_x(x_{ij})$ of each pixel values as (2):

$$\mu_x(x_{mn}) = \begin{cases} \frac{1}{1 + |x_{mn} - \mu_0|/C}, & x_{mn} \leq t \\ \frac{1}{1 + |x_{mn} - \mu_1|/C}, & x_{mn} > t \end{cases} \quad (2)$$

$$C = \min\{|t - \mu_0|, |t - \mu_1|\} \quad (3)$$

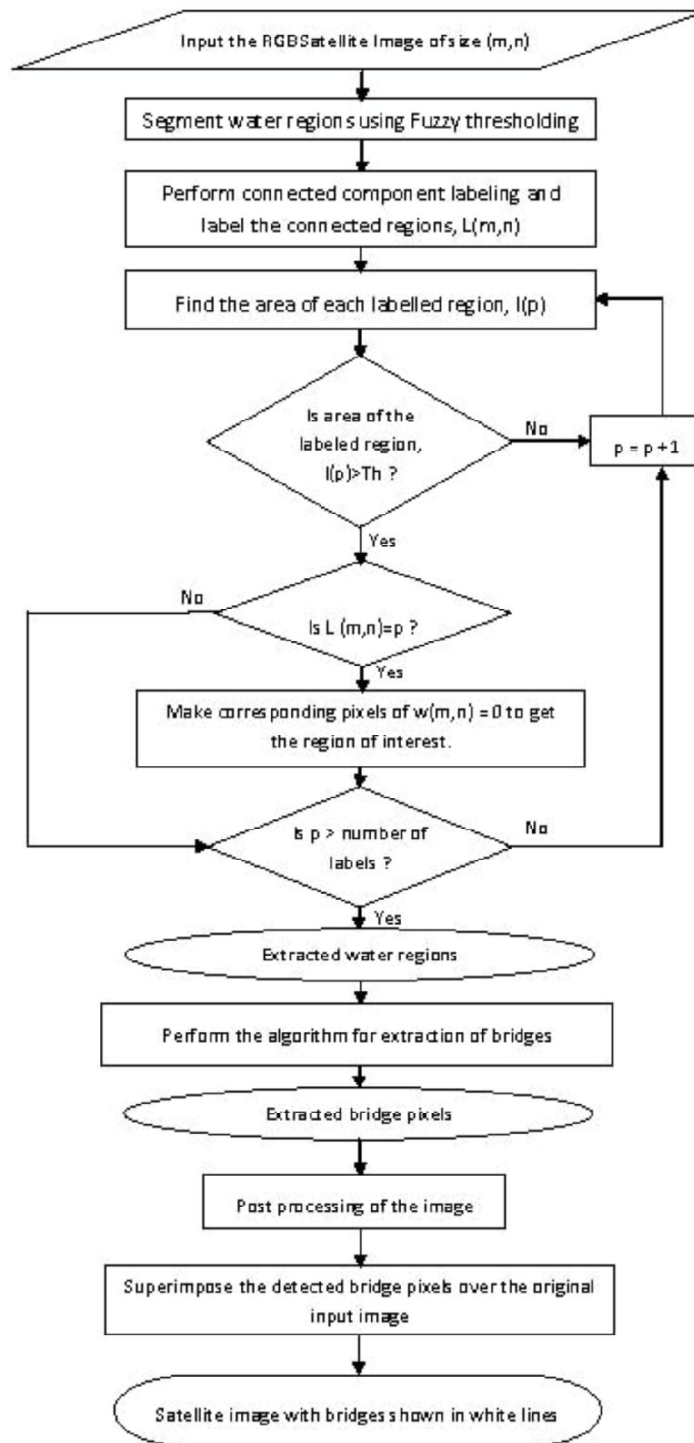


Fig. 7. Schematic diagram of the method

where μ_0 is the average gray value of background ($x_{ij} \leq t$) and μ_1 is average gray value of foreground ($x_{ij} > t$). Then find the expectation value for all threshold values using equation (4).

$$E(X, A) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (2 \times \mu_X(x_{mn}) - 1) \quad (4)$$

The t corresponding to the minimum of all expectation values is selected as the optimum threshold for that particular image. The fuzzy segmented image for the test image shown in fig.1 is given in fig.8.

B. Fine segmentation to remove noise

By a sequence of morphological erosion and dilation steps undesired small objects are removed and the bridge gaps are closed. Binary morphological operators such as erosion and dilation combine a local neighborhood of pixels with a pixel mask to achieve the desired result. The output pixel, 0, is set to either a hit (1) or a miss (0) based on the logical AND relationship. Therefore the operation uses the following (5) as its mask:

$$B = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (5)$$

The remaining image region is now the expectation area of bridges over water bodies. The expectation area can be further scaled down by a logical exclusive OR operation with the initial threshold result and subsequent noise reduction. Figure 9 shows the result of fine segmented image.



Fig. 8. Fuzzy segmented image



Fig. 9. Fine segmented image

C. Area Analysis

After morphological operations, there are still a lot of regions which are similar to water areas. The size of these areas are very small compared to other regions and can be eliminated by connected component labelling. To verify the hypothesized connected components as water regions, area analysis is performed. A suitable threshold for area is determined by using Otsu's method [9] and this is applied for the fine segmented image. Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum. This can be achieved by finding a threshold with the maximum between class variance and minimum within class variance. This can be calculated by the following equations (6 and 7).

$$\text{Within Class Variance } \sigma_w^2 = W_b \sigma_b^2 + W_f \sigma_f^2 \quad (6)$$

$$\begin{aligned}
\text{Between Class Variance } \sigma_B^2 &= \sigma^2 - \sigma_w^2 \\
&= W_b (\mu_b - \mu)^2 + W_f (\mu_f - \mu)^2 \\
&\quad (\text{where } \mu = W_b \mu_b + W_f \mu_f) \\
&= W_b W_f (\mu_b - \mu_f)^2 \tag{7}
\end{aligned}$$

where weight, mean and variance are represented by w , μ and σ . The foreground and background regions are distinguished as f and b . After otsu's thresholding regions having area size greater than the threshold is considered as the region of interest which is shown in fig.10.



Fig. 10. Image after area analysis

D. Extraction of bridges

Bridges are extracted from the image using the logic that at bridge edges there is a transition between black and white pixels. If the number of pixels between the transitions is less than at least 10% percentage of width of the image for an 1-m resolution image, they are considered as bridge pixels. But if the resolution of the satellite image varies this threshold is modified accordingly. The algorithm is formulated as follows (Table.1):

Using the algorithm any type of bridges are extracted irrespective of their inclination angle, shape and size. As the algorithm is carefully formulated without considering the geometrical features, further processing is not much required in the test process. The below figures (Fig.11) show the extracted bridge regions and the detected edge lines of the bridge.



Fig. 11. Extracted bridge regions and the detected edge lines of the bridge

TABLE I: BRIDGE EXTRACTION ALGORITHM

1. Start
2. Initialize the ROI segmented image as $B(i,j)$
3. Set $i=0$ & $j=0$
4. Set Flag =0
5. Check whether there is a 0 to 1 transition in $B(i,j)$
6. If Yes, Set the Flag
7. Check whether there is a 1 to 0 transition in $B(i,j)$
8. If Yes, find the number of pixels between two transitions
9. If it is less than 10% of $B(i,j)$, record the pixels between two transitions
10. Reset the Flag
11. Increment j and repeat steps 5 to 9
12. Increment i and repeat steps 4 to 11
13. Stop

E. Post processing of the extracted image

The output image includes error specified by the scattered white points which may be detected as bridges. This can be eliminated using improved hough transform [10]. Compared with traditional HT, the improvements are consisted of normalizing parameter space, eliminating spurious peaks, determining end points according to dynamic clustering rule. Figure 12 shows the result of improved hough transform. Finally superimpose the detected bridge pixels over the original input image. Satellite PS-MS image with bridges shown in white pixels is the resultant image (Figure 13).

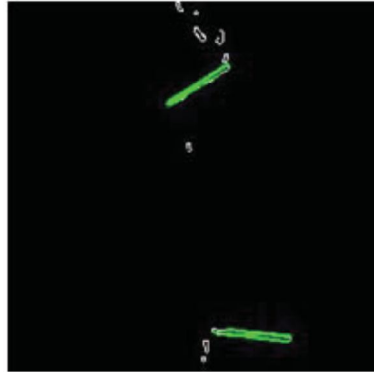


Fig. 12. Image after post processing



Fig. 13. Resultant image

IV. APPLICABILITY OF THE SAME ALGORITHM USING NDWI

Instead of using fuzzy thresholding, we have utilized the possibility of clustering using NDWI for ROI extraction as the method specified in E. Gediket. al., 2012 [8]. They have mentioned in their work itself that it is not always possible to distinguish water from shadows using the proposed approach as water and shadow have similar reflectance characteristics, but it still give better results than simple thresholding. Except that we have not made any changes in our method of bridge detection and the same fully automatic bridge detection algorithm is applied for the multispectral test images and both results are compared. Figure 14 shows ROI extraction of water segment for the PS-MS image in fig.1 using both methods. We can see that the method using fuzzy thresholding have superior performance.



Fig. 14. Region of Interest extraction: (a) Proposed Method (b) Using NDWI

The miss detections seen as black spots in the background of the segmented image using NDWI is because of some other areas having low reflectance values as that of water region in the original image. Though this is rectified to a certain extent in the area analysis phase, the bridge detected image is not as good as that of our method. The results are shown in fig.15.

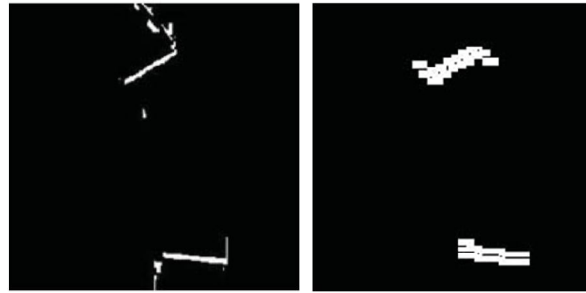


Fig15: Extracted Bridge regions (a) Proposed Method (b) Using NDWI



Fig16: Resultant Bridge detected Image of fig.1 (a) Proposed Method (b) Using NDWI

The bridge detected results using both methods for the multispectral images in fig 1 and fig.4 are given in fig. 16 and 17 respectively.

The results obtained for other RGB test images of different resolutions using our proposed method are given in fig.18 to fig.21.

V. RESULT ASSESSMENT AND DISCUSSIONS

The proposed algorithm has been tested on various images obtained from different satellite sensors and the outputs are obtained with considerable accuracy. The algorithm proposed here uses fuzzy based segmentation and Otsu's thresholding for area analysis, which increase the applicability of this work over a wide range of images since the threshold is not fixed. These two methods find out the most suitable threshold for each



Fig17: Resultant Bridge detected Image of fig.4 (a) Proposed Method (b) Using NDWI



Fig. 18. Bridge detected IKONOS image (1-m)



Fig. 19. Bridge detected Quickbird image (60-cm)



Fig. 20. Bridge detected IKONOS image (1-m)



Fig. 21. Bridge detected SPOT5 image (4-m)

image according to the statistical properties of the image. This algorithm is designed to perform on images of varying resolutions. Using the algorithm any type of bridges are extracted irrespective of their inclination and shape. Also segmentation is not affected by gray level values which changes with elevation angle of sun and turbidity of water. Satellite images obtained in spatial domain as well as spectral domain can be processed using this method. While comparing the proposed method with the method using NDWI for ROI extraction, we can see that the method developed in our work is superior.

VI. CONCLUSION

In this paper, a fuzzy based automatic bridge detection technique is designed for any type of satellite images including low resolution images, images taken at different sun azimuth and elevation angles and images having bridges of different angle of inclinations. Considering the results, acceptable accuracy for the resultant images is obtained and so the efficiency of the bridge detection process is improved by using our algorithm. But this method is suitable only for bridges over water. Using Digital Elevation Model (DEM) obtained for the region, it can be possible to distinguish bridges over water and other bridges or spanning roads. Future works include developing algorithms for spanning road detection also.

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